2019 IEEE Intelligent Vehicles Symposium (IV)
Paris, France. June 9-12, 2019

Transferable Driver Behavior Learning via Distribution Adaption in the Lane Change Scenario*

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***Abstract*—Because of the high accuracy and low cost, learning-based methods have been widely used to model driver behaviors in various scenarios. However, the performance of learning-based methods depend heavily on the quantity and coverage of the driving data. When the new driver with insufficient data is considered, the accuracy of these methods cannot be guaranteed any more. To solve this problem, the balanced distribution adaptation (BDA) is used to build the new driver's decision making model in the lane change (LC) scenario. Meanwhile, a transfer learning (TL) based regression model, modified BDA (MBDA) is proposed to predict the driver's steering behavior during the LC maneuver. Cross validation (CV) based model selection (MS) method is developed to obtain the optimal parameters in model training process. A series of experiments are carried out based on the simulated and naturalistic driving data to verify the TL based classification and regression models. The experimental results indicate that the BDA and MBDA have an outstanding ability in knowledge transfer. Compared with support vector machine (SVM) and Gaussian mixture regression (GMR), the proposed methods show a better performance in the decision making of lane keep/change and the prediction of the driver's steering operation.**

I. Introduction

Many researchers focus on the data-driven methods using machine learning algorithms due to their flexibility and adaptability. Traditional data-driven methods are proposed and developed using statistical learning [1, 2], deep learning [3-6], reinforcement learning [7] and hybrid dynamics systems [8-10] in various scenarios, such as, lane change, car following and obstacle avoidance.

In [11] and [12], the on road naturalistic driving data is collected to analysis the driver's lane change behaviors, which pays more attention on the interaction between the ego vehicle and surrounding vehicles from an vehicle trajectory perspective. To solve the Multivariate Time Series (MTS) problem in lane change scenarios, [13] proposed to recognize the lane change intention by Group-wise Convolutional Neural Network (MTS-GCNN) based on three types of driving information. [14] proposed a framework by combining the hidden Markov model (HMM) and Bayesian filtering (BF) to build the driver's lane change decision making model. A steering angles predictor based on adaptive fuzzy neural network (AFNN) is proposed by [15] to predict the lane change behaviors based on a high fidelity simulator. In [7], a reinforcement learning (RL) based framework is proposed to learning the driver specific behavior in the overtaking scenario.

With the development of the data science, the learning based data driven methods can recognize and predict the driver behavior with a high accuracy and a minor error. But the driver model built by data driven methods is personalized and performs well on the specific driver. The adaptation of models between different drivers with characteristic differences is difficult, which leads to the high demand of the number of the specific-driver data. In many practical situations, the implicit assumption of driving data is hard to be satisfied due to the time consuming in data collection, data process and data labeling. How to build the personalized and specific driver model with sufficient historical driving data and insufficient driving data for the new driver is the key to develop the learning based data driven methods. In this paper, we propose to solve the problems above based on the transfer learning methods.

The definition of transfer learning is to transfer the knowledge or parameters from one domain (source domain) to another different but similar domain (target domain) and solve the problem in new domain when the two domains are in different but relevant feature and distribution [16]. The reason why we research and apply transfer learning is to speed up the learning process or improve the model in the new different domain with insufficient training data. As a new learning framework to address the machine learning problem, transfer learning earns a great success in classification [17], image recognition [18], wifi localization [19], robot models [20], deep learning and reinforcement learning [21]. As for the intelligent vehicle (IV), [7] proposed the modified local procrustes analysis (MLPA) based on the manifold alignment (MA) to build the driver model in the overtaking scenarios, which accurately predicted the driver's steering operation with insufficient driving data. In [22], the secondary driving tasks are recognized by "fine-turning" the

*This work was supported by the National Natural Science Foundation of China under Grant 61703041, SAIC Motor Industry-University-Research Collaboration Project and Key Laboratory of Biomimetic Robots and Systems, Beijing Institute of Technology, Ministry of Education (Project Grant No. 2017CX02005).

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convolutional neural network (CNN), which transfers the pre-trained CNN's parameters to speed up the training process. In [23], reinforcement learning (RL) is combined with transfer learning to update the policy of lane keep, lane change and obstacle avoidance in target domain. It performs better than traditional RL methods in the new target environment. In this paper, BDA is introduced to recognizing the target driver's lane change/lane keep (LC/LK) decision making by considering both marginal distribution and conditional distribution [24]. To predict the driver's steering behavior by regression model, MBDA is proposed to build the target driver's steering model with insufficient driving data.

The main contributions of this paper are as follows:

1. Build the target driver's LC/LK decision making model with insufficient driving data based on transfer learning based method-BDA.
2. Considering to exactly predict the new driver's steering behavior, modified BDA (MBDA) is proposed to build the transfer learning based driver's steering model. It provides an effective method to build the personalized driver model for new driver with insufficient driving data.
3. To avoid selecting the model's parameters manually, cross validation (CV) based model selection (MS) method, CVMS, is developed to obtain the optimal parameters.

II. PROBLEM FORMULATION

A. The Lane Change Scenario and Driver Model

The lane change scenario considered in this paper is shown in figure 1.

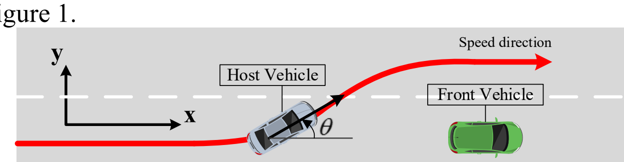


Figure 1. The lane change scenario

A successful lane change behavior relies on the driver's action of operating the steering wheel. The driver model built in this paper only focus on the lateral control of the host vehicle. In order to establish the lane change driver model for the LC/LK decision making and the steering operation, the state at time step t, as the input of the model, is defined as below.

$$\mathbf{s}_t = [x_{h,t}, y_{h,t}, \theta_{h,t}, x_{f,t}, y_{f,t}, v_{h,t}, \alpha_{h,t}] \tag{1}$$

Where $x_{h,t}$ and $y_{h,t}$ represent the longitudinal and the lateral position of the host vehicle at time step t, similarly, $x_{f,t}$ and $y_{f,t}$ are longitudinal and the lateral distance of the front vehicle at time step t. The four states above can influence the driver's cognition of the relative location of two vehicles. $\theta_{h,t}$, $v_{h,t}$ and $\alpha_{h,t}$ represent the heading angle, velocity and steering wheel angle of host vehicle at time step t, respectively.

In this paper we only concentrate on the lateral control of the vehicle, so the output for the driver model are LC/LK decision making d_t and steering wheel angle (SWA) $\alpha_{h,t+1}$ according to the current states. In lane change scenario, the decision making is about whether or not to make a lane change and the action is the driver's SWA. Thus, we can define the action of the model at time step t as:

$$d_t = \begin{cases} 0, & lane \;\; keep \\ 1, & lane \;\; change \end{cases} \tag{2}$$

$$a_t = \alpha_{h,t+1} \tag{3}$$

Where d_t is the LC/LK decision making value.

B. Transfer learning

In order to build a personalized driver model for a specific driving behavior with a high accuracy in inferring or predicting, as much as possible situation should be covered as the training data for the data driven method. However, data collection is time consuming and has several limitations:

1. Sensor-based data collection for naturalistic driving data is expensive. The analysis process is always time consuming, which includes manually extracting situation from useful and useless driving data [25, 26].
2. Data collection in simulation environment is efficient and relatively economic. Since there is an inherent difference between the simulated scenario and the naturalistic scenario, the data collected in simulation cannot completely describe the real road condition.
3. The driver model built by the personalized driving data collection and analysis only fit the single driver whose driving data is collected and analyzed. The model's performance decrease rapidly for another driver's driving data. Therefore, for a new driver with few driving data, the personalized driver model has limited ability in adaptation and generalization.

The target of transfer learning is to transfer instance level knowledge from source domain (sufficient data) to target domain (insufficient data) and solve the specific problem in target domain. If sufficient driving data is collected for the target driver, the transfer learning based methods are not needed. In this paper, we mainly focus on the situation that the classification and regression model are built by insufficient driving data from the target driver and sufficient driving data from source driver.

As for classification problem, BDA is introduced to recognize the target driver's LK/LC decision making. But for the prediction of the steering wheel angle, which is the continuous variables, no label is provided for the model's calculation. Based on the general BDA, a modified BDA (MBDA) is proposed to solve the regression for the target driver's steering wheel angle.

III. METHOD

To solve the problems discussed above, two driver models are developed based on BDA: lane change/keep decision-making model and the driver's steering model. In order to obtain the driver's steering model, an adaptive transfer learning method, modified BDA (MBDA), is proposed. Finally, considering that model's parameters are distinct in different cases, which is time consuming to select the ideal parameters manually, we proposed a cross validation (CV) based method CVMS to obtain the optimal parameters.

A. Classification

For the difference of distribution between driver models, we use transfer-learning method to adapt the domain of two drivers' driving data, which is called domain adaption. Domain adaption aims to adapt the different domains usually by adapting marginal or conditional distribution to reduce the distance between two domains. For the purpose of minimizing the error brought by the model transferring, the difference of both marginal and conditional distribution between driver models are considered. And Thus, we introduce Balanced Domain Adaption (BDA)[27], a transfer learning method, to train the classifier. BDA adapts both marginal and conditional distributions between domains with a balance factor μ to weight the importance of distributions so as to reduce the distance between two domains:

$$D(\mathcal{D}_s, D_t) \approx (1-\mu)D(P(\mathbf{s}_s), P(\mathbf{s}_t)) + \mu D(P(y_s \mid \mathbf{s}_s), P(y_t \mid \mathbf{s}_t)) \tag{4}$$

By adopting maximum mean discrepancy (MMD) to evaluate the distance, the equation can then be written as:

$$\begin{aligned} D(\mathcal{D}_s, \mathcal{D}_t) \approx (1-\mu)\left\| \frac{1}{n}\sum_{i=1}^{n}\mathbf{s}_{s_i} - \frac{1}{m}\sum_{j=1}^{n}\mathbf{s}_{t_j} \right\|_{\mathcal{H}}^2 \\ +\mu\sum_{c=1}^{C}\left\| \frac{1}{n_c}\sum_{\mathbf{s}_{s_i}\in\mathcal{D}_s^{(c)}}\mathbf{s}_{s_i} - \frac{1}{m_c}\sum_{\mathbf{s}_{t_j}\in\mathcal{D}_t^{(c)}}\mathbf{s}_{t_j} \right\|_{\mathcal{H}}^2 \end{aligned} \tag{5}$$

Where $\mathcal{D}_s^{(c)} = \{\mathbf{s}_i : \mathbf{s}_i \in \mathcal{D}_s \wedge d(\mathbf{s}_i) = c\}$ is the set of examples belonging to class c in the source domain, $d(\mathbf{s}_i)$ is the decision making value according to the current state $\mathbf{s}_i$, and $n_c = \left|\mathcal{D}_s^{(c)}\right|$. $\mathcal{D}_t^{(c)} = \{\mathbf{s}_j : \mathbf{s}_j \in \mathcal{D}_t \wedge \hat{d}(\mathbf{s}_j) = c\}$ is the set of examples belonging to class c in the target data, where $\hat{d}(\mathbf{s}_j)$ is the soft label of $\mathbf{s}_j$ using K-Nearest Neighbor(KNN) trained by source data, and $m_c = \left|\mathcal{D}_t^{(c)}\right|$.Then this problem can be described as an optimization problem:

$$\begin{aligned} &\min tr(\mathbf{A}^T\mathbf{S}((1-\mu)\mathbf{M}_0 + \mu\sum_{c=1}^{C}\mathbf{M_c})\mathbf{S}^T\mathbf{A}) + \lambda\|\mathbf{A}\|_F^2 \\ &s.t. \mathbf{A}^T\mathbf{SHS}^T\mathbf{A} = \mathbf{I}, 0 \le \mu \le 1 \end{aligned} \tag{6}$$

Where $\mathbf{S} = [\mathbf{s}_s, \mathbf{s}_t]$ and λ is the regularization parameter. $\mathbf{I} \in \mathcal{R}^{(n+m)\times(n+m)}$ is the identity matrix, $\mathbf{H} = \mathbf{I} - (\frac{1}{n})\mathbf{1}$ is the centering matrix. $\mathbf{M}_0$ and $\mathbf{M_c}$ are the MMD matrix of marginal and conditional distribution, respectively, which can be calculated as follows:

$$(M_0)_{ij} = \begin{cases} \frac{1}{n^2}, & \mathbf{s}_i, \mathbf{s}_j \in \mathcal{D}_s \\ \frac{1}{m^2}, & \mathbf{s}_i, \mathbf{s}_j \in \mathcal{D}_t \\ -\frac{1}{mn}, & \textit{otherwise} \end{cases} \tag{7}$$

$$(M_c)_{ij} = \begin{cases} \frac{1}{n_c^2}, & \mathbf{s}_i, \mathbf{s}_j \in \mathcal{D}_s^{(c)} \\ \frac{1}{m^2}, & \mathbf{s}_i, \mathbf{s}_j \in \mathcal{D}_t^{(c)} \\ -\frac{1}{m_c n_c}, & \begin{cases} \mathbf{s}_i \in \mathcal{D}_s^{(c)}, \mathbf{s}_j \in \mathcal{D}_t^{(c)} \\ \mathbf{s}_i \in \mathcal{D}_t^{(c)}, \mathbf{s}_j \in \mathcal{D}_s^{(c)} \end{cases} \\ 0 & \text{otherwise} \end{cases} \tag{8}$$

Using the Lagrange Multiplier Method, the Lagrange multiplier is defined as $\mathbf{\Phi} = (\phi_1, \phi_2, ..., \phi_d)$. And the Lagrange function is:

$$\begin{aligned} L = tr(\mathbf{A}^T\mathbf{S}((1-\mu)\mathbf{M}_0 + \mu\sum_{c=1}^{C}\mathbf{M_c})\mathbf{S}^T\mathbf{A}) \\ +\lambda\|\mathbf{A}\|_F^2 + tr((\mathbf{A}^T\mathbf{SHS}^T\mathbf{A} - \mathbf{I})\Phi) \end{aligned} \tag{9}$$

The optimization process is derived as a generalized Eigen decomposition problem at $\frac{\partial L}{\partial \mathbf{A}} = 0$:

$$(\mathbf{S}((1-\mu)\mathbf{M}_0 + \mu\sum_{c=1}^{C}\mathbf{M_c})\mathbf{S}^T) + \lambda\mathbf{I})\mathbf{A} = \mathbf{SHS}^T\mathbf{A}\Phi \tag{10}$$

The transformation matrix $\mathbf{A}$ is obtained by solving the equation above. With the transformation matrix $\mathbf{A}$ the adaptive states can be presented as $\mathbf{S}_{new} = \mathbf{A}^T\mathbf{S}$, which can be taken as the input in the next iteration. In each iteration, $\mathbf{A}$ as well as the soft labels is updated. The soft label will be more similar to the target driver with the iteration and thus contributes to the performance of the next iteration. After the iteration, without further calculation we can output the latest soft labels as the decision of the driver's LK/LC model.

B. Regression

In order to predict the SWA of target driver according to the current driving state s at time t, a transfer learning based regression model is needed. However, BDA is developed for classification, which cannot solve the regression problem. The action value (label) in regression problem is enormous, which cause $\mathcal{D}_s^{(c)}$ to be overfitting. Conditional distribution part $\mu\sum_{c=1}^{C}\mathbf{M_c}$ in (6) is difficult to calculate and inaccurately composed. Therefore, we proposed an adaptive transfer learning method MBDA to build the transfer learning regression model by generating pseudo labels to substitute the regression value in BDA and solve the computational and overfitting problem. Using MBDA, the data in source domain and target domain can be adapted by forming a new target domain that is enlarged with sufficient labeled data from source domain. Traditional regression model GMR is then introduced to learn the driver's steering model under the enlarged target domain.

To generate pseudo labels for source data, we applied Gaussian Mixture Model (GMM), an unsupervised classification model. And GMM can be presented as follows:

$$p(\xi_j) = \sum_{k=1}^{K}\pi_k\mathcal{N}(\xi_j; \boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k) \tag{11}$$

Where $\xi_j = [\mathbf{s}_j, \mathbf{a}_j, \mathbf{d}_j]^T$ is the feature matrix and K is the components of the mixture models. $\{\pi_k, \boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k\}$ are the parameters of Gaussian component $\boldsymbol{\theta}_k$, in which π_k is the prior probability, $\boldsymbol{\mu}_k$ is the mean vector and $\boldsymbol{\Sigma}_k$ is the covariance matrix.

The parameters of GMM can be estimated using standard expectation maximization (EM) algorithm while apply k-means to set an initial estimate and avoid being trapped into a poor local minimum. Pseudo labels of source data $\hat{\mathbf{a}}_s$ is then generated with GMM:

$$\hat{\mathbf{a}}_s = \arg\max_{1 \le l \le k} \{\Pr(l \mid \xi_s)\}. \tag{12}$$

With pseudo labels $\hat{\mathbf{a}}_s$ substituting the SWA $\mathbf{a}_s$, we can apply BDA to adapt the domain of two driver models. The distance can then be calculated using (5) where $\mathcal{D}_s^{(c)} = \{\mathbf{s}_i : \mathbf{s}_i \in \mathcal{D}_s \wedge \hat{a}(\mathbf{s}_i) = c\}$ and $\mathcal{D}_t^{(c)} = \{\mathbf{s}_j : \mathbf{s}_j \in \mathcal{D}_t \wedge \hat{\hat{a}}(\mathbf{s}_j) = c\}$. With MMD matrixes composed, we can acquire transferred matrix $\mathbf{A}$ by solving (10). The states in the new domain can be represented as $\mathbf{S}_{new} = \mathbf{A}^T\mathbf{S} = \mathbf{A}^T[\mathbf{s}_s, \mathbf{s}_t] = [\mathbf{s}_{snew}, \mathbf{s}_{tnew}]$. We then consider this new domain as new target domain and apply traditional regression model GMR under this new domain for the regression problem.

Parameter of Gaussian component $\boldsymbol{\theta}_k$ can be acquired by training set $\xi_s = [\mathbf{s}_{snew}, \mathbf{a}_s, \mathbf{d}_s]^T$. In each GMM model, the input and output parameters are separated the mean and covariance matrix can be defined as:

$$\boldsymbol{\mu}_k = \{\boldsymbol{\mu}_{i,k}, \boldsymbol{\mu}_{o,k}\}$$
$$\boldsymbol{\Sigma}_k = \begin{pmatrix} \boldsymbol{\Sigma}_{i,k} & \boldsymbol{\Sigma}_{io,k} \\ \boldsymbol{\Sigma}_{oi,k} & \boldsymbol{\Sigma}_{o,k} \end{pmatrix}, \tag{13}$$

The expectation of SWA of target driver model $a_{te,i}$ at time step i given $\hat{\xi}_j$ and $\boldsymbol{\theta}_k$ can then be iteratively calculated as:

$$\hat{\xi}_{o,k} = \left(\boldsymbol{\mu}_{o,k} + \boldsymbol{\Sigma}_{oi,k}(\boldsymbol{\Sigma}_{i,k})^{-1}(\mathbf{s}_i - \boldsymbol{\mu}_{i,k})\right), \tag{14}$$

$$h_k = \frac{\pi_k \mathcal{N}(\hat{\xi}_i; \boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k)}{\sum_{k'=1}^{K} \pi_k \mathcal{N}(\hat{\xi}_i; \boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k)}, \tag{15}$$

$$a_{te,i} = \sum_{k=1}^{K} h_k \hat{\xi}_{o,k}. \tag{16}$$

C. Cross validation based model selection

Several parameters are adjustable in the regression and classification model while the chosen of model parameters has a great influence on the accuracy of transfer learning model. However, it is time-consuming to manually select the weight factor μ, the regularization parameter λ and the number of GMM components K. Cross validation (CV) based method, CVMS, is developed to select the optimal model parameters $\Pi^{(n)} = \{\mu^{(n)}, \lambda^{(n)}, K^{(n)}\}$. The risk is then defined as:

$$\hat{R}_{kCV}^{(n)} \equiv \frac{1}{k}\sum_{j=1}^{k} \frac{1}{|\mathcal{T}_j|} \sum_{(\mathbf{s},a,d) \in \mathcal{T}_j} l(a, d, \hat{f}_{\mathcal{T}_j}(\mathbf{s})), \tag{17}$$

where $\varsigma = [\mathbf{s}_{tnew,t}, \mathbf{a}_t, \mathbf{d}_t]^T$ is the new target set and is randomly divided into k subsets $\{\varsigma_i\}_{i=1}^{k}$. $\hat{f}_{\mathcal{T}_j}(\mathbf{s})$ is the prediction for $\mathbf{s} \in \mathcal{T}_j$ using driver model trained by T_{train} where $\mathcal{T}_j = \{\varsigma_i\}_{i \ne j}$ is the testing set and $T_{train} = [\varsigma_j, \xi_s]$ is the training set.

The loss function $l(\cdot)$ for the classification model is the accuracy of recognition. For the regression model, root mean square error (RMSE) is chosen as the loss function,

$$l^r(a, \hat{f}_{\mathcal{T}_j}(\mathbf{s})) = \sqrt{\frac{1}{m}\sum_{i=1}^{m}\left(\hat{f}_{\mathcal{T}_j}(\mathbf{s}_i; \Pi^{(n)}) - a_i\right)^2}. \tag{18}$$

By minimizing the risk of the model, we can acquire the optimized parameters:

$$(\mu_{CV}, \lambda_{CV}, K_{CV}) = \arg\min_{\Pi} R_{kCV}^{(n)}(\mu^{(n)}, \lambda^{(n)}, K^{(n)}). \tag{19}$$

IV. Experiment

In this section, the data collection and data processing procedure are introduced to collect and extract the driving data in lane change scenario. Two experiments (classification and regression) are conducted by the collected driving data to verify the proposed methods. The result of two experiments are described and analyzed by comparing to the method without transfer learning.

A. Data collection

In order to conduct the experiments, data collection in lane change scenario is necessary. To collect the driving data for model training efficiently, we build a simulated environment using the platform of PRESCAN/SIMULINK to simulate the driving environment. The frequency of collection is 100Hz. The driver's operation is collected by Logitech G29 equipment and send into the simulated vehicle dynamic system. The visualized driving environment will be feedback to the driver by monitors. Under the simulated environment, a lane change scenario is designed for different drivers to perform lane change. During data collection procedure, three drivers with different driving ages are asked to operate the lane change based on their own driving style and experience in a near constant speed.

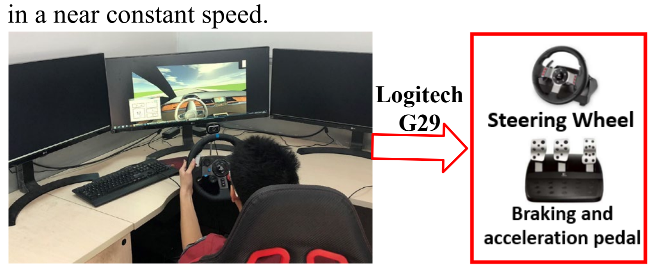


Figure 2. Data collection in simulated environment.

The naturalistic data is also collected and applied to verify the accuracy of the BDA model, which transfer the knowledge from virtual to real. The naturalistic data used in this experiment is obtain from the public UAH DriverSet [28, 29]. Three drivers' LC behaviors with different states are extracted manually from the whole dataset by the playback software.

B. The analysis for different drivers

As section II mentioned, different drivers have different driving behaviors in conducting a lane change operation and the transfer learning methods are used to reduce the error caused by different domains (source domain and target domain). This difference can be observed from the data collected from above simulated environment in data perspective. As Figure 3 shows, in the same lane change scenario, different drivers conduct the lane change behavior in their own style. Comparing to driver1&driver3, driver 2 tends to operate lane change sharper and with a greater steering wheel angle up to 50 deg, while driver3 prefers to make a lane change later compared to the other two drivers. These differences between drivers can cause great error when use the personalized driver model trained by a single driver and the transfer learning methods is applied and developed to reduce the error caused by model gap.

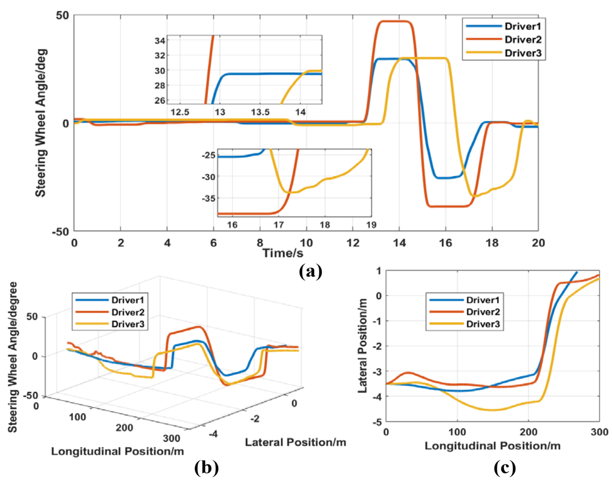


Figure 3. The comparision between different drivers.

For the reason that driver cannot give accurate indication about their lane change decisions, we need to manually label the collected driving data for the driver's decision making model in the lane change scenario. We define the lane change data as a series of data that has rapidly changing steering wheel angle and has a latent displacement that is close to a lane width. Considering the complexity of the road condition that a trajectory may not be flat and strait, we assume that steering wheel angle in the start of a lane change process may not equals to the end of it. Thus we label the start and end of a lane change where they equal to their nearest stable value and have a minimum distance between them. Then data of the lane change process are labeled as lane-changing (LC) while the rest of them are labeled as lane-keeping (LK).

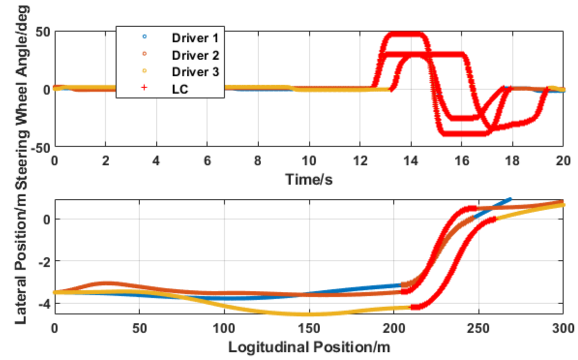


Figure 4. The result of LK/LC labelling for different drivers.

C. Driver lane change/keep decision-making model

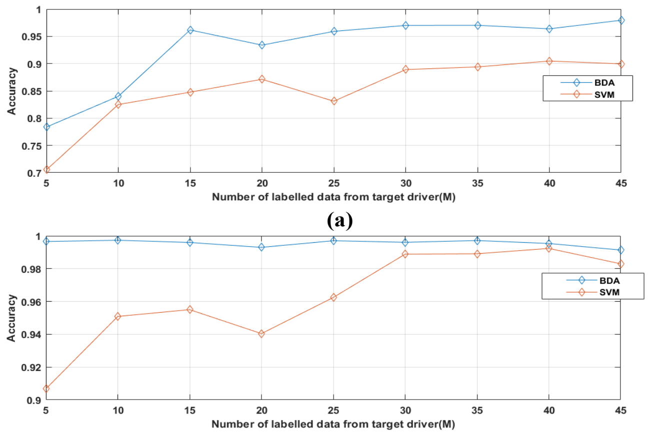
Our target is to build a driver model that can efficiently assist the driver in making better decisions in the lane change scenario. To build a personalized driver model, we can collect sufficient data for the driver or use data from the other drivers, but either method is accessible enough. In this paper, the transfer learning based LK/LC decision-making model is proposed to avoid the high cost of massive data collection and obtain high accuracy with insufficient target driver's driving data. In the first experiment, both simulated driving data (driver1, driver 2 and driver 3) and naturalistic driving data (driver R) are applied to validate the lane change/keep decision-making model.

The training set is composed of the sufficient source driving data and insufficient target data. The rest data from target set are used as testing set. CV is used to choose the optimal model parameters. μ is chosen from $\{0, 0.1, 0.2, ..., 1.0\}$ and λ is chosen from $\{0.01, 0.05, 0.1, 0.5, 1, 5, 10, 50, 100\}$.

Except for recognizing the LK/LC decision based on simulated driving data, the model also recognize the LK/LC decision based on the naturalistic driving data. Table I presents results of the transfer learning based decision making model with simulate driving data. Noticing the gap between the real environment and the virtual environment, the performance of virtual to real decision making model is presented at Table II.

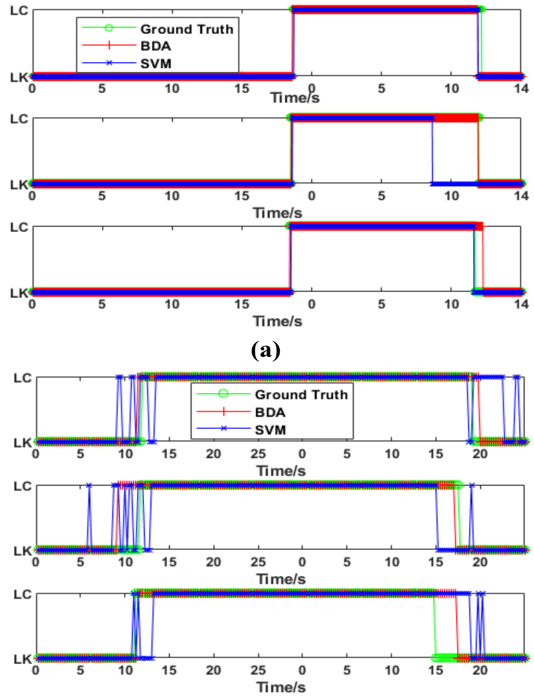
Figure 5 illustrates the result of exp.1 in Table I. The target samples are the training data obtained from the target domain with insufficient driving data. Although SVM and BDA can achieve a high accuracy with a large M, BDA can easily surpass SVM with insufficient target driving data ($M \leq 30$). When there are only few labeled data from target driver are used in training set ($M \leq 30$), BDA obviously has a better performance than SVM. And the performance of BDA is stable at a very high level with an accuracy over 99% even if only few data from target driver are considered, while the performance of SVM relies on the labelled data from target driver. Overall, the transfer learning based driver decision making model have a good performance in reducing the error caused by driver differences and model gap.

In Table II, compared to the experiment conducted by simulated driving data, the error of the experiment from virtual to real is higher. As shown in Figure 5, with $M = 10 \sim 30$, both BDA and SVM in fig.5(a) have a relative low accuracy about 0.7~0.8, while both methods have a higher accuracy in fig.5 (b) over 0.9 with the same M. With the increasing of M, the accuracy of BDA and SVM increase, but they cannot reach a high level of 0.99 in fig.5(a) and fig.5(b). Moreover, as to the transfer learning from virtual to real, BDA obtains a high accuracy (0.95) than SVM (0.90) with $M > 30$. It indicates that BDA can minish the error caused by the difference between virtual and real. Figure 6 illustrates the recognizing results for continuous time series driving data with different M.



(a) (b)

Figure 5. Comparison of BDA and SVM. (a) transfer from virtual to real (b) transfer between simulated driving data.



(a) (b)

Figure 6. The recognizing results of LK/LC by SVM and BDA with

TABLE I. EXPERIMENTAL RESULTS FOR DRIVER LC/LK MODEL FOR SIMULATED DRIVING DATA

The Number of Target Samples			10	20	30	40	50	60	70	80	90
1	Driver 1 to 2	BDA (%)	99.65	99.73	99.60	99.30	99.70	99.61	99.71	99.53	99.13
		SVM (%)	90.68	95.09	95.50	94.04	96.24	98.88	98.91	99.23	98.30
2	Driver 1 to 3	BDA (%)	98.03	97.78	97.09	98.34	97.61	98.26	98.24	97.89	98.30
		SVM (%)	84.39	84.58	87.14	83.91	86.81	85.95	87.54	86.07	87.31
3	Driver 2 to 1	BDA (%)	99.37	98.95	99.82	99.39	99.80	99.29	99.54	99.29	99.49
		SVM (%)	97.79	98.20	97.64	98.36	97.83	99.13	98.33	99.03	99.22
4	Driver 2 to 3	BDA (%)	98.58	98.61	98.66	98.63	97.84	98.37	98.71	98.61	98.86
		SVM (%)	88.36	89.42	90.74	90.56	89.90	91.61	91.09	92.46	94.03
5	Driver 3 to 1	BDA (%)	90.29	93.23	94.95	91.66	96.35	94.79	95.49	97.22	97.10
		SVM (%)	79.81	80.20	81.60	84.08	77.82	81.55	82.61	83.11	84.05
6	Driver 3 to 2	BDA (%)	93.06	95.17	97.45	95.20	94.17	97.95	98.01	97.95	97.55
		SVM (%)	84.17	87.15	88.05	91.59	88.42	89.89	92.23	91.85	91.64

TABLE II. EXPERIMENTAL RESULTS FOR DRIVER LC/LK MODEL FROM VIRTUAL TO REAL

The Number of Target Samples			10	20	30	40	50	60	70	80	90
1	Driver 1 to Driver R	BDA (%)	78.37	84.00	96.17	93.39	95.91	97.00	97.02	96.38	97.95
		SVM (%)	70.53	82.50	84.77	87.13	83.11	88.91	89.40	90.48	89.95
2	Driver 2 to Driver R	BDA (%)	82.45	84.92	94.72	94.96	97.42	96.27	97.21	97.43	95.41
		SVM (%)	76.33	82.50	84.09	88.17	87.47	89.45	90.05	90.57	89.07
3	Driver 3 to Driver R	BDA (%)	83.35	93.58	91.15	95.65	94.93	98.27	96.93	96.48	97.37
		SVM (%)	74.69	86.33	82.13	85.83	87.11	92.09	90.70	89.14	90.05
4	Driver R to Driver 1	BDA (%)	78.90	82.12	89.37	96.69	95.99	96.18	97.72	97.64	96.55
		SVM (%)	82.47	81.76	85.19	89.89	92.41	91.86	91.78	95.04	94.08
5	Driver R to Driver 2	BDA (%)	77.65	86.46	93.02	95.12	97.02	97.05	96.45	95.16	97.95
		SVM (%)	75.37	83.17	87.91	89.93	91.72	92.18	94.36	93.11	95.46
6	Driver R to Driver 2	BDA (%)	74.41	94.00	93.63	94.71	94.11	97.43	97.14	95.63	97.24
		SVM (%)	77.75	90.36	91.57	93.75	93.42	92.71	93.20	94.00	95.84

different M. From top to bottom, M equals 10, 20, 30. Ground Truth in (a) is the LK/LC label of driver 1 data and in (b) the Ground Truth is the LK/LC label of driver R.

D. Driver steering model

Our target is to build the driver steering model based on transfer learning method, which is a regression problem and only acquire insufficient target driver's driving data. So we proposed MBDA based on BDA to solve the regression problem. The model training procedure is similar to the procedure of LK/LC decision making model. The optimal model parameters are chosen by CVMS with $\mu \in \{0, 0.1, 0.2, ..., 1.0\}$, $\lambda \in \{0.01, 0.05, 0.1, 0.5, 1, 5, 10, 50, 100\}$, $K \in \{3, 4, 5, 6\}$.

Table III presents the prediction error for SWA between each two drivers. Model parameters chosen by CVMS in this experiment are $K = 5$, $\mu = 0.2$ and $\lambda = 10$. As illustrated in fig.7, with $M < 30$, MBDA (TL) performs better than GMR (without TL), which presents the superiority of transfer learning. Only with sufficient data from target driver (M>30), GMR can achieve a relatively low error (0.2 deg) which surpass the MBDA (0.8 deg). Figure 8 shows the steering wheel angle generated in experiment 1 at Table III, the sufficient driver 1's data and insufficient driver 2's data are used to predict the SWA of driver 2 with M=10. In this experiment, the MBDA predict the SWA of driver 2 with lower error (RMSE) than GMR without transfer learning.

The driver steering model have a good performance even when only few target driver's driving data are used in training set. And with the increasing number of data from target driver used in model training process, the error of driver steering model decreased. Although the model using only GMR can achieve a very great performance with sufficient target driver's driving data, the cost of data collection is high for an improvement of RMSE around 0.6 deg.

V. Conclusion And Future Work

In this paper, a transfer learning based classification model is introduced and applied to model the driver's LK/LC decision making in lane change scenario. Meanwhile, in order to solve the regression problem and predict the driver's operation on steering wheel, the modified BDA is proposed. Both the marginal and conditional distribution is considered to minimize the difference between the distributions of different drivers and overcome the model gap between them. Cross validation based model selection method, CVMS, is developed to obtain the optimal model parameters, which provides a model selection method for TL based driver model. The experimental results based on simulated and naturalistic driving data indicate that TL based driver models perform better than traditional driver model (without transfer learning). The two TL-based driver models provide a new way to build the driver model with insufficient driving data, which has a great significance in reducing the cost of data collection.

Our future works will focus on reducing the computation time and improving the model's adaptation in complicated scenarios.

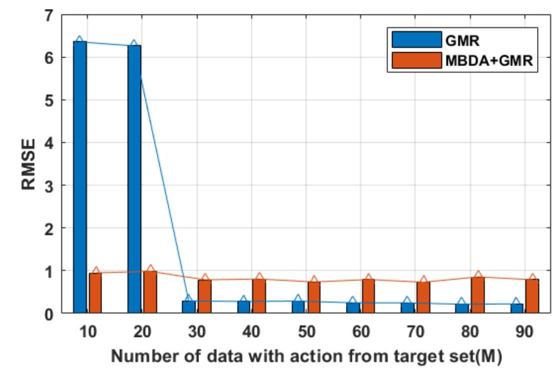


Figure 7. Comparision of prediction (Driver 1 to 2) result of two method at different M.

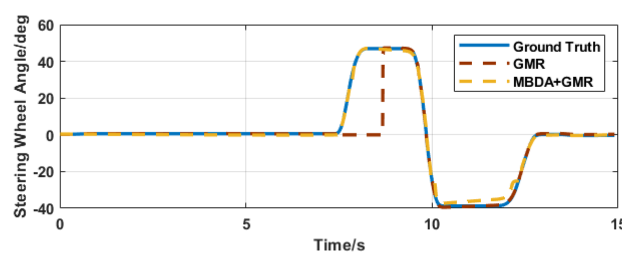


TABLE III. Experimental Results for Driver Steering Model

The Number of Target Samples			10	20	30	40	50	60	70	80	90
1	Driver 1 to 2	MBDA-GMR	0.95	0.98	0.79	0.81	0.74	0.79	0.73	0.86	0.79
		GMR	6.35	6.26	0.29	0.28	0.29	0.25	0.25	0.22	0.22
2	Driver 1 to 3	MBDA-GMR	1.85	1.63	1.21	1.19	1.15	1.30	1.17	1.08	1.06
		GMR	3.54	0.30	0.29	0.23	0.23	0.18	0.17	0.16	0.19
3	Driver 2 to 1	MBDA-GMR	1.12	1.03	0.97	1.00	1.00	0.94	1.00	0.92	0.91
		GMR	9.91	4.29	0.27	2.77	0.27	0.21	0.18	0.18	0.20
4	Driver 2 to 3	MBDA-GMR	1.11	1.01	0.96	0.92	0.79	0.95	0.83	0.79	0.82
		GMR	14.41	2.61	3.90	3.18	1.12	0.34	1.23	0.47	0.26
5	Driver 3 to 1	MBDA-GMR	0.60	0.51	0.61	0.47	0.50	0.49	0.39	0.50	0.46
		GMR	9.12	4.18	3.75	1.89	1.33	1.79	0.22	1.10	0.24
6	Driver 3 to 2	MBDA-GMR	17.58	5.11	5.30	2.61	5.40	2.37	1.22	2.10	0.27
		GMR	0.96	0.94	0.96	0.96	0.92	0.90	0.88	0.87	0.87

Figure 8. Result of prediction (Driver 1 to 2) at M=10.

REFERENCES

[1] T. Taniguchi, S. Nagasaka, K. Hitomi, N. P. Chandrasiri, and K. Takenaka, "Sequence Prediction of Driving Behavior Using Double Articulation Analyzer," *IEEE Transactions on Systems Man & Cybernetics Systems,* vol. 46, no. 9, pp. 1300-1313, 2016.

[2] T. Taniguchi, F. Kai, H. Liu, Y. Tanaka, and T. Bando, "Determining Utterance Timing of a Driving Agent With Double Articulation Analyzer," *IEEE Transactions on Intelligent Transportation Systems,* vol. 17, no. 3, pp. 1-11, 2015.

[3] J. Zheng, K. Suzuki, and M. Fujita, "Car-following behavior with instantaneous driver-vehicle reaction delay: a neural-network-based methodology," *Tramsportation Research Part C Emerging Technologies,* vol. 36, no. 11, pp. 339-351, 2013.

[4] C. Colombaroni and G. Fusco, "Artificial Neural Network Models for Car Following: Experimental Analysis and Calibration Issues," *I V H S Journal*.

[5] J. Morton, T. A. Wheeler, and M. J. Kochenderfer, "Analysis of Recurrent Neural Networks for Probabilistic Modeling of Driver Behavior," *IEEE Transactions on Intelligent Transportation Systems,* vol. 18, no. 5, pp. 1289-1298, 2017.

[6] W. Xiao, J. Rui, L. Li, Y. Lin, X. Zheng, and F. Y. Wang, "Capturing Car-Following Behaviors by Deep Learning," *IEEE Transactions on Intelligent Transportation Systems,* vol. PP, no. 99, pp. 1-11, 2018.

[7] C. Lu, F. Hu, W. Wang, and J. Gong, "Transfer Learning for Driver Model Adaptation via Modified Local Procrustes Analysis," no. Iv, 2018.

[8] K. Jong-Hae *et al.*, "Modeling of driver's collision avoidance maneuver based on controller switching model," *IEEE Transactions on Systems Man & Cybernetics Part B Cybernetics A Publication of the IEEE Systems Man & Cybernetics Society,* vol. 35, no. 6, pp. 1131-43, 2005.

[9] H. Okuda, N. Ikami, T. Suzuki, Y. Tazaki, and K. Takeda, "Modeling and Analysis of Driving Behavior Based on a Probability-Weighted ARX Model," *IEEE Transactions on Intelligent Transportation Systems,* vol. 14, no. 1, pp. 98-112, 2013.

[10] S. Sekizawa *et al.*, "Modeling and Recognition of Driving Behavior Based on Stochastic Switched ARX Model," *IEEE Transactions on Intelligent Transportation Systems,* vol. 8, no. 4, pp. 593-606, 2007.

[11] H. Zhao, C. Wang, Y. Lin, F. Guillemard, S. Geronimi, and F. Aioun, "On-Road Vehicle Trajectory Collection and Scene-Based Lane Change Analysis: Part i," *IEEE Transactions on Intelligent Transportation Systems,* vol. 18, no. 1, pp. 192-205, 2017.

[12] W. Yao *et al.*, "On-Road Vehicle Trajectory Collection and Scene-Based Lane Change Analysis: Part II," *IEEE Transactions on Intelligent Transportation Systems,* vol. 18, no. 1, pp. 206-220, 2017.

[13] J. Gao, Y. L. Murphey, and H. Zhu, "Multivariate time series prediction of lane changing behavior using deep neural network," *Applied Intelligence,* vol. 48, no. 10, pp. 3523-3537, 2018/10/01 2018.

[14] K. Li, X. Wang, Y. Xu, and J. Wang, "Lane changing intention recognition based on speech recognition models," *Transportation Research Part C: Emerging Technologies,* vol. 69, no. November 2015, pp. 497-514, 2016.

[15] J. Tang, F. Liu, W. Zhang, R. Ke, and Y. Zou, "Lane-changes prediction based on adaptive fuzzy neural network," *Expert Systems with Applications,* vol. 91, pp. 452-463, 2018/01/01/ 2018.

[16] S. J. Pan and Q. Yang, "A survey on transfer learning," *IEEE Transactions on Knowledge and Data Engineering,* vol. 22, no. 10, pp. 1345-1359, 2010.

[17] Q. Y. G.-R. X. Y. Y. Wenyuan Dai, "Boosting for Transfer Learning," *Proceedings of the 24th International Conference on Machine Learning,* vol. 53, pp. 187-204, 1997.

[18] D. Han, Q. Liu, and W. Fan, "A new image classification method using CNN transfer learning and web data augmentation," *Expert Systems with Applications,* vol. 95, pp. 43-56, 2018.

[19] P. Sinno Jialin, I. W. Tsang, J. T. Kwok, and Y. Qiang, "Domain Adaptation via Transfer Component Analysis," *IEEE Transactions on Neural Networks,* vol. 22, no. 2, pp. 199-210, 2011.

[20] B. Bocsi, L. Csato, and J. Peters, "Alignment-based transfer learning for robot models," *Proceedings of the International Joint Conference on Neural Networks,* no. August 2015, 2013.

[21] H. Yin and S. J. Pan, "Knowledge Transfer for Deep Reinforcement Learning with Hierarchical Experience Replay," *Association for the Advancement of Artificial Intelligence (AAAI 2017),* pp. 1640-1646, 2017.

[22] Y. Xing *et al.*, "End-to-End Driving Activities and Secondary Tasks Recognition Using Deep Convolutional Neural Network and Transfer Learning," *IEEE Intelligent Vehicles Symposium, Proceedings,* vol. 2018-June, no. Iv, pp. 1626-1631, 2018.

[23] Z. Xu, C. Tang, and M. Tomizuka, "Zero-shot Deep Reinforcement Learning Driving Policy Transfer for Autonomous Vehicles based on Robust Control," *The 21st IEEE International Conference on Intelligent Transportation Systems,* pp. 2865-2871, 2018.

[24] J. Wang, Y. Chen, S. Hao, W. Feng, and Z. Shen, "Balanced distribution adaptation for transfer learning," *Proceedings - IEEE International Conference on Data Mining, ICDM,* vol. 2017-Novem, pp. 1129-1134, 2017.

[25] J. Xue *et al.*, "BLVD: Building A Large-scale 5D Semantics Benchmark for Autonomous Driving," 2019.

[26] W. Maddern, G. Pascoe, C. Linegar, and P. J. T. I. J. o. R. R. Newman, "1 year, 1000 km: The Oxford RobotCar dataset," vol. 36, no. 1, pp. 3-15, 2017.

[27] J. Wang, Y. Chen, S. Hao, W. Feng, and Z. Shen, "Balanced Distribution Adaptation for Transfer Learning," presented at the 2017 IEEE International Conference on Data Mining (ICDM), 2017.

[28] E. Romera, L. M. Bergasa, and R. Arroyo, "A Real-time Multi-scale Vehicle Detection and Tracking Approach for Smartphones," in *IEEE International Conference on Intelligent Transportation Systems*, 2015.

[29] E. Romera, L. M. Bergasa, and R. Arroyo, "Need data for driver behaviour analysis? Presenting the public UAH-DriveSet," *IEEE Conference on Intelligent Transportation Systems, Proceedings, ITSC,* pp. 387-392, 2016.